What attributes influence the selection of a romantic partner?

PREDICT 422 - Section 56 - Group 2
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Data

- Sourced from Kaggle

- Compiled by Columbia Business School professors Ray Fisman and Sheena Iyengar for their paper title “Gender Differences in Mate Selection: Evidence From a Speed Dating Experiment.”

Additional Data Info

- Data was gathered from participants in experimental speed dating events from 2002-2004. During the events, the attendees would have a four minute "first date" with every other participant of the opposite sex. At the end of their four minutes, participants were asked if they would like to see their date again. They were also asked to rate their date on six attributes: Attractiveness, Sincerity, Intelligence, Fun, Ambition, and Shared Interests.
- The dataset also includes questionnaire data gathered from participants at different points in the process. These fields include: demographics, dating habits, self-perception across key attributes, beliefs on what others find valuable in a mate, and lifestyle information. See the Speed Dating Data Key document below for details.

Sample Survey Question

We want to know what you look for in the opposite sex.
Waves 1-5, 10-21: You have 100 points to distribute among the following attributes -- give more points to those attributes that are more important in a potential date, and fewer points to those attributes that are less important in a potential date. Total points must equal 100.

Attractive	+
Sincere	+
Intelligent	+
Fun	+
Ambitious	+
Shared Interests	+
	100

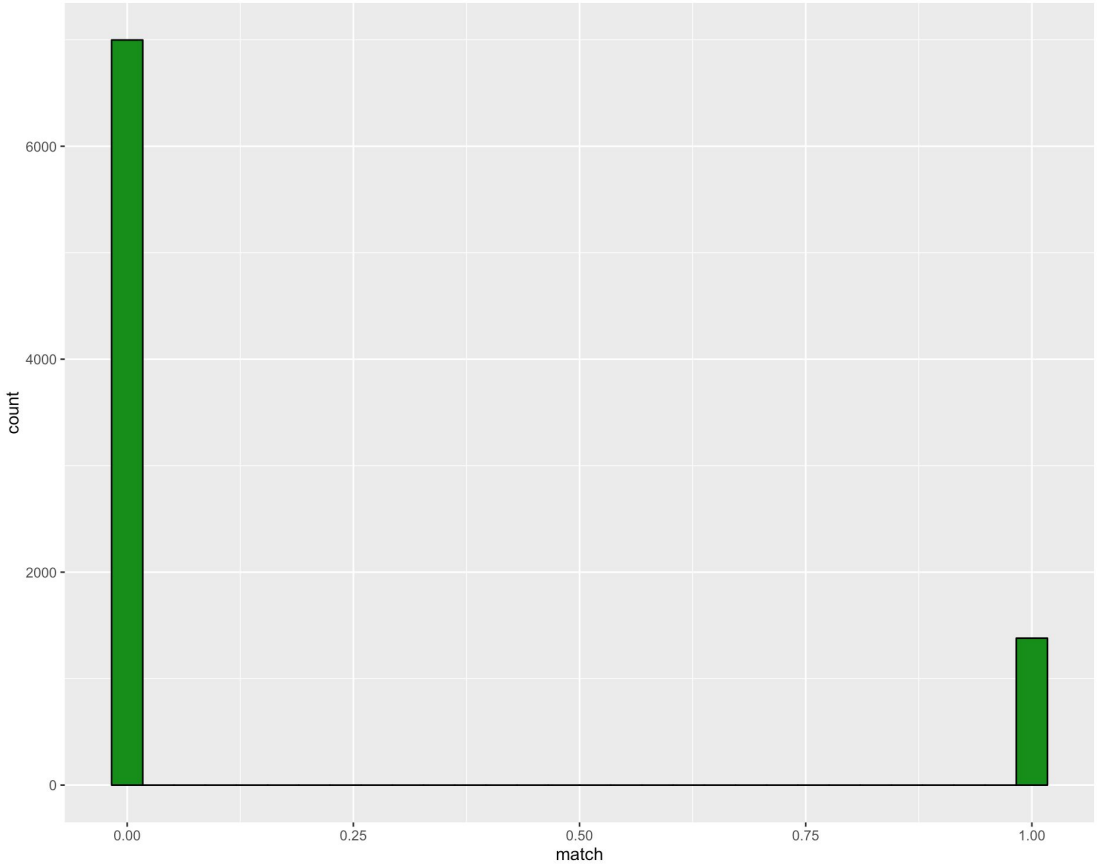
attr1_1
Attractive
sinc1_1
Sincere
intel1_1
Intelligent
fun1_1
Fun
amb1_1
Ambitious
shar1_1
Has shared interests/hobbies

EDA - INITIAL FINDINGS

- There was not a single line of data that was “complete”.
  - Lots of missing data!
  - Noticed that for a majority of the follow up questions, the data was missing at a higher rate.
  - For simplicity’s sake, decided to focus on variables gathered through the pre-date survey.
    - Demographics, interests, attributes they find important.
  - Additionally, limited to only the waves that used the same preference scale (score from 1-100)
  - Performed listwise deletion instead of imputation to handle missing.
- Data went from 8378 rows with 195 variables (sparsely populated) to 6521 rows with 51 variables (complete).

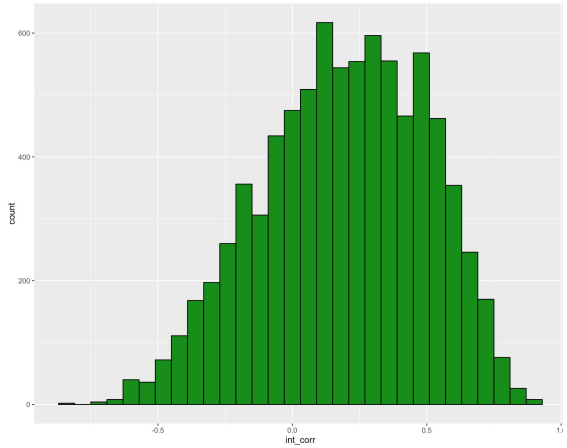
EDA - Response Variable

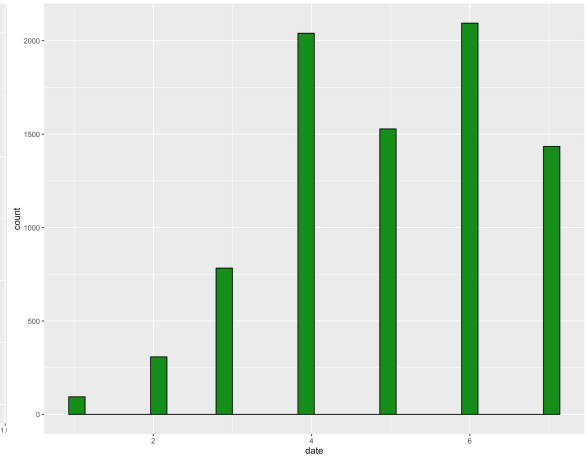
- Much fewer matches than non-matches.
- As we'll see in the end results, this greatly impacts our model's ability to successfully predict whether a date will end in a match.
- Classification problem

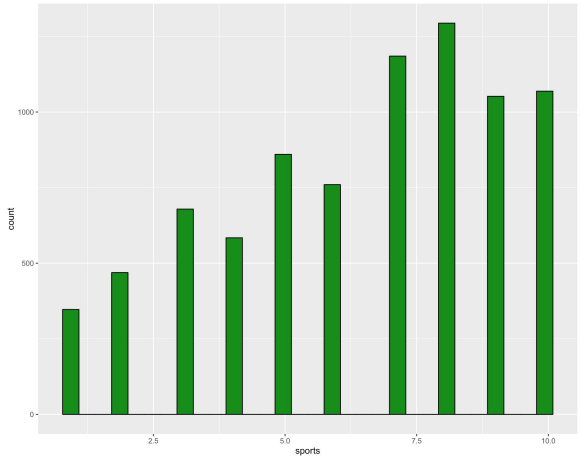


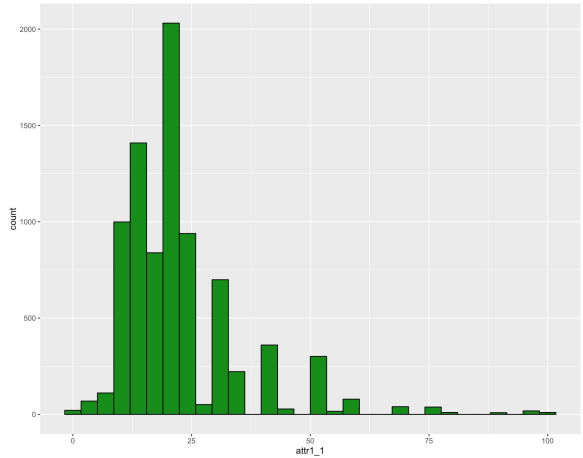
EDA - Input Variables

- Demographics: gender, age of participant, age of partner, race of participant, race of partner
- Initial Correlation between interests
- How frequently the participants goes out, on dates & generally.
- What participant is looking for: Date, Meet people, etc.
- Interests: For example, sports
- What the participants looks for in the opposite sex.
- What the participants thinks the opposite sex looks for.
- What participant thinks of themselves.





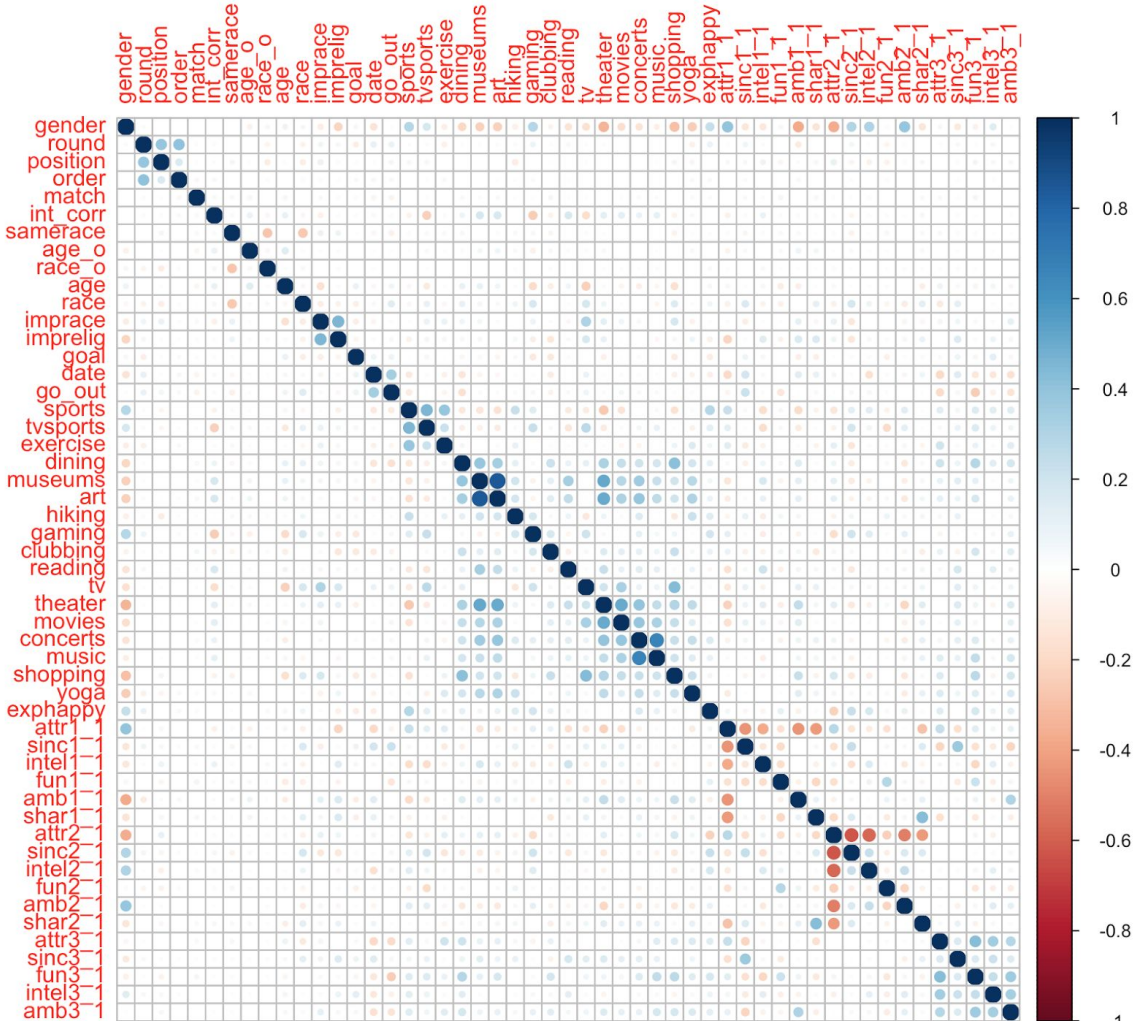




Analysis - Correlations

- No variables are even moderately correlated with the response variable, “match”.

- However, some variables are moderately correlated with one another:
  - For example, if someone ranks art as an interest, they are likely to also be interested in museums and theater. Same goes for music and concerts, and theater and movies.
  - Additionally, if someone thinks the opposite sex finds sincerity important, they are likely to believe they do not find attractiveness important in their partner.


gender
round
position
order
match
int_corr
samerace
age_o
race_o
age
race
imprace
imprelig
goal
date
go_out
sports
tvsports
exercise
dining
museums
art
hiking
gaming
clubbing
reading
tv
theater
movies
concerts
music
shopping
yoga
exphappy
attr1_1
sinc1_1
intel1_1
fun1_1
amb1_1
shar1_1
attr2_1
sinc2_1
intel2_1
fun2_1
amb2_1
shar2_1
attr3_1
sinc3_1
fun3_1
intel3_1
amb3_1
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
-1

Modeling - Preparation

- We are trying to predict whether a date will result in a “match” -- an outcome of 1 or 0.
- Split data into train and test data sets.
  - Train is approximately 75% of the data, test is the remaining 25%.
- Center and Scale data to have mean of 0 and stddev of 1
- Classification Techniques Attempted:
  - Logistic Regression using stepwise variable selection
  - K Nearest Neighbor Classification
  - Random Forest
  - Support Vector Machine

Modeling: Stepwise Logistic

- A majority of the variables are removed during the stepwise variable selection process.
- Additionally, observing the variance inflation factors of the remaining variables in the stepwise logistic model, all of the attributes representing what the participants believe the opposite sex thinks is important have values well above 10 and will be removed from the final model.

```
> vif(step.glm)
   gender     order  int_corr  samerace     age_o       age   imprace      date    go_out    dining   museums
 2.140385  1.011482  1.090534  1.040206  1.045940  1.162631  1.105335  1.292842  1.227202  1.384723  4.389361
      art  clubbing   reading    movies  concerts   attr1_1   sinc1_1   shar1_1   attr2_1   sinc2_1  intel2_1
 4.097239  1.124215  1.235381  1.371002  1.424144  2.502898  1.569047  1.595997 84.721625 17.696489 15.015277
   fun2_1    amb2_1   shar2_1   attr3_1    amb3_1
14.962845 14.890252 12.787696  1.310381  1.231207
```

Modeling: Stepwise Logistic

- Using a threshold of 0.35, an optimal accuracy can be achieved at 83.9%.
- The sensitivity is AWFUL for this model.
    - It basically cannot seem to find any separating features to distinguish a match.

```
> confusionMatrix(glm.pred,test.std$match,positive='1')
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0 1362  254
         1    9    6

               Accuracy : 0.8387
                 95% CI : (0.82, 0.8563)
    No Information Rate : 0.8406
    P-Value [Acc > NIR] : 0.5964

                  Kappa : 0.0267
 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.023077
            Specificity : 0.993435
         Pos Pred Value : 0.400000
         Neg Pred Value : 0.842822
             Prevalence : 0.159411
         Detection Rate : 0.003679
   Detection Prevalence : 0.009197
      Balanced Accuracy : 0.508256

       'Positive' Class : 1
```

```
Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.68542    0.04077 -41.341  < 2e-16 ***
gender       0.05605    0.04536   1.236 0.216519
order       -0.08676    0.03980  -2.180 0.029280 *
int_corr     0.11081    0.04065   2.726 0.006411 **
samerace     0.10619    0.03912   2.714 0.006643 **
age_o       -0.11250    0.04118  -2.732 0.006298 **
age         -0.16609    0.04384  -3.789 0.000151 ***
imprace     -0.13133    0.04148  -3.166 0.001545 **
date        -0.10904    0.04289  -2.542 0.011020 *
go_out      -0.09475    0.04635  -2.044 0.040936 *
dining       0.10886    0.04764   2.285 0.022303 *
museums     -0.19399    0.08171  -2.374 0.017589 *
art          0.17841    0.07932   2.249 0.024508 *
clubbing     0.10192    0.04159   2.450 0.014268 *
reading      0.07368    0.04415   1.669 0.095131 .
movies      -0.14499    0.04399  -3.296 0.000982 ***
concerts     0.10529    0.04705   2.238 0.025246 *
attr1_1     -0.15592    0.05524  -2.822 0.004767 **
sinc1_1     -0.08600    0.04718  -1.823 0.068345 .
shar1_1     -0.13738    0.04478  -3.068 0.002158 **
attr3_1      0.07290    0.04513   1.615 0.106227
amb3_1      -0.06253    0.04313  -1.450 0.147103
```

Modeling: KNN

- This model performs slightly better on the test set when using k=7.
- The model does really good at predicting a “no match” scenario, but is still struggling capturing the “match” scenario.
- 83.9% accuracy is pretty good.

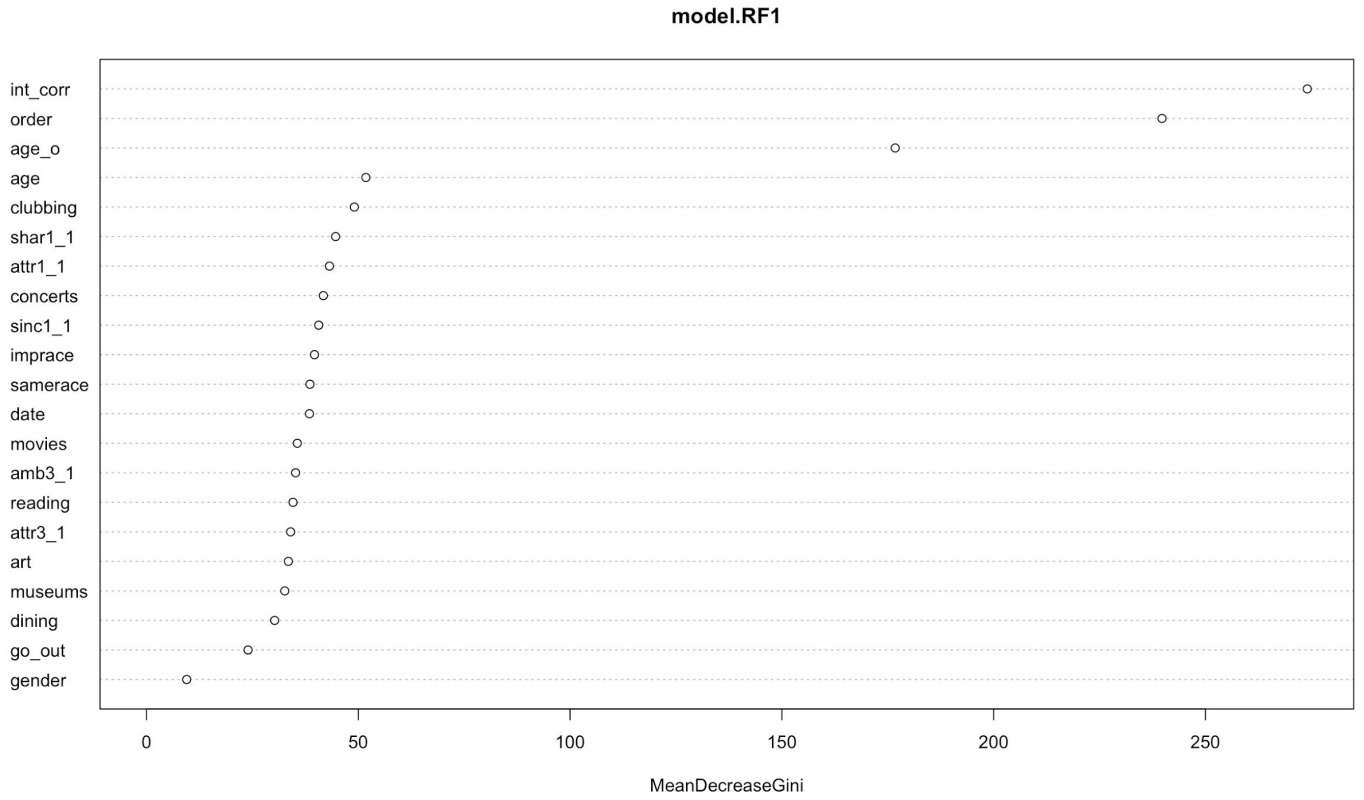
```
> confusionMatrix(knn.pred,test.std$match,positive='1')
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0 1325  216
         1   46   44

               Accuracy : 0.8394
                 95% CI : (0.8206, 0.8569)
    No Information Rate : 0.8406
    P-Value [Acc > NIR] : 0.5701

                  Kappa : 0.1846
 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.16923
            Specificity : 0.96645
         Pos Pred Value : 0.48889
         Neg Pred Value : 0.85983
             Prevalence : 0.15941
         Detection Rate : 0.02698
   Detection Prevalence : 0.05518
      Balanced Accuracy : 0.56784

       'Positive' Class : 1
```

Modeling: Random Forest

- This model performs slightly worse than the KNN approach at 82.9% test accuracy.
- Although accuracy is less than the logistic, it does a better job of predicting a match.

```
> confusionMatrix(pred.RF1,test.std$match,positive='1')
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0 1315  223
         1   56   37

               Accuracy : 0.8289
                 95% CI : (0.8098, 0.8469)
    No Information Rate : 0.8406
    P-Value [Acc > NIR] : 0.9055

                  Kappa : 0.1372
 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.14231
            Specificity : 0.95915
         Pos Pred Value : 0.39785
         Neg Pred Value : 0.85501
             Prevalence : 0.15941
         Detection Rate : 0.02269
   Detection Prevalence : 0.05702
      Balanced Accuracy : 0.55073

       'Positive' Class : 1
```

Modeling: Random Forest Variable Importance



Modeling: SVM Tuning

```
> svm.tune=tune(svm,match~.,data=train.std ,kernel ="radial",ranges =list(cost=c(0.001 , 0.01, 0.1, 1,5,10,100) ))
> summary(svm.tune)

Parameter tuning of 'svm':

- sampling method: 10-fold cross validation

- best parameters:
 cost
    1

- best performance: 0.1487436

- Detailed performance results:
   cost     error dispersion
1 1e-03 0.1548789 0.01421086
2 1e-02 0.1547604 0.01419352
3 1e-01 0.1536157 0.01400667
4 1e+00 0.1487436 0.01315632
5 5e+00 0.1535722 0.01430075
6 1e+01 0.1611456 0.01625275
7 1e+02 0.2342837 0.02226606
```

Modeling: SVM

- The support vector machine is comparable in that it has an accuracy of 83.3%. However, it still is not very good at predicting our target class of “match”.

```
> confusionMatrix(pred.svm$flag,test.std$match,positive='1')
Confusion Matrix and Statistics

          Reference
Prediction    0    1
         0 1332  235
         1   39   25

               Accuracy : 0.832
                 95% CI : (0.813, 0.8498)
    No Information Rate : 0.8406
    P-Value [Acc > NIR] : 0.8368

                  Kappa : 0.0975
 Mcnemar's Test P-Value : <2e-16

            Sensitivity : 0.09615
            Specificity : 0.97155
         Pos Pred Value : 0.39062
         Neg Pred Value : 0.85003
             Prevalence : 0.15941
         Detection Rate : 0.01533
   Detection Prevalence : 0.03924
      Balanced Accuracy : 0.53385

       'Positive' Class : 1
```

And the best model is...

- Considering performance in terms of accuracy on the test set alone, one would most likely select the KNN classification model.
- However, considering the interpretability of the random forest (i.e having the variable importances to look back on), one might decide to sacrifice a little bit of accuracy for the insight into what lead an observation to be classified the way that it was.

Reflection/Summary/Conclusion

- The best model for accuracy isn't always the most interpretable one.
- For support vector machines, it is helpful to leverage R's parallel processing capabilities to speed things up.
- When the data is so heavily skewed towards one class, it throws a wrench into an otherwise classic classification problem.
- Although Gender was speculated as being a variable that impacts whether or not someone gets a match or not, it isn't very important in the random forest and it's not significant at all in the logistic regression.
- Doing this again, we would work on grouping the interests into components representing the category of interest.

Code

- Full project code can be found here: https://github.com/amsheets/PREDICT422_GroupECProject